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AI-Mediated Communication in E-Commerce: Implications for Customer Trust

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ABSTRACT

Generative artificial intelligence (AI) technologies offer new potential for marketing and customer operations, such as automation and personalization of customer service. However, more must be understood about how AI-mediated communication (AI-MC) affects customer trust. We conducted an online experiment to investigate the impact of AI-MC on customer trust in an online retail context. We presented $N=294$ participants with two email scenarios describing a product return context, labeled as written by either (a) a service employee, (b) a service employee assisted by AI, or (c) AI on behalf of the service employee. We further varied levels of service criticality to consider customers' perception of vulnerability. Our findings revealed higher customer trust ratings in the online retailer when the email communications were written by the service employee, compared to those written by the service employee assisted by AI. When analyzing the different components of trust, it was found that communications written by the service employee assisted by AI reduced perceptions of both the online retailer's benevolence and integrity, while communications written by AI on behalf of the employee led to lower perceived integrity of the online retailer. Surprisingly, service criticality did not affect trust ratings. We discuss the managerial implications of integrating generative AI into customer service in the context of the EU AI Act, which came into force on 1 August 2024.

1 | Introduction

With the release of ChatGPT-3 in November 2022 (Crawford et al. 2023), a new era has begun. Artificial intelligence (AI) chatbots can now generate answers that are language-wise correct, compelling, and hard to distinguish from human-generated content (Mei et al. 2024). Due to its ease of use and potential to increase efficiency, ChatGPT has been widely adopted in both private (Thormudsson 2023a) and business contexts (Thormudsson 2023b). In marketing and customer relationship management (CRM; i.e., interactions and processes facilitated by a business to manage and nurture relationships with customers through the integration of people, processes, and technology; Chen and Popovich 2003), the enormous business potential of generative AI (i.e., AI systems that can autonomously generate content, such as text or images, using advanced machine learning models trained on large datasets; Kaplan and Haenlein 2019) is reflected in exceptionally high adoption rates (Dencheva 2023; Thormudsson 2023b), for instance, for automatizing customer communication in social media and email messaging (Schweidel et al. 2023). Under the EU AI Act, which came into force on 1 August 2024, European companies are obliged to label AI-generated content and make its use transparent for their customers (European Commission 2024).

Brief abstracts of these findings have been submitted for presentation at the 53rd Congress of the German Psychological Society (DGPs)/15th Conference of the Austrian Psychological Society (ÖGP) 2024, 16-19 September and at the 22nd Congress of Work and Organizational Psychology (EAWOP) 2025, 21-24 May.

Such regulations reflect a broader international discourse on AI governance, highlighting the need to adapt legal frameworks, including data security and protection, as well as strengthen ethical foundations in response to the challenges posed by AI (Al Najdawi et al. 2024, 2025). This raises the question of how customers react toward the explicit use of AI and AI-mediated communication (AI-MC) in marketing and CRM and whether transparency about AI usage enhances or undermines customer trust (Bakonyi 2024; Sigala et al. 2024).

Previous studies showed that customers are often skeptical when interacting with AI. For instance, customer purchase rates dropped by nearly 80% when the identity of an AI chatbot was revealed at the beginning of a sales call compared to when the identity of the AI chatbot was not disclosed (Luo et al. 2019). A recent study by Liu et al. (2022) showed that individuals mistrust the sender of an email dealing with a product inquiry when the email has been written with the help of AI. Research on the "Word-of-Machine" effect suggests that customers' preferences for AI or human recommendations depend on whether the decision context is utilitarian or hedonic. Customers perceive AI as more competent than humans for utilitarian tasks but less so for hedonic tasks (Longoni and Cian 2020). This highlights that AI-driven recommendations in utilitarian settings may foster trust, while they could erode trust in hedonic scenarios. Further evidence suggests that customers tend to mistrust AI, especially in situations of high service criticality, that is, when the outcome of a service interaction is significant to the customer (Chen et al. 2022; Xu, Shieh, et al. 2020). High service criticality often leads to increased customer vulnerability, as the outcomes of service interactions can significantly impact customers' well-being or satisfaction (Dehghanpouri et al. 2020). Mozafari et al. (2021) found that if service criticality is high, disclosing a chatbot's identity as such negatively affected customer trust in the conversational partner, while customer trust was not impaired when service criticality was low. This aligns with findings from Logg et al. (2019), who discovered that despite initial concerns about algorithmic decisions, individuals often exhibit *algorithm appreciation*, meaning they trust algorithmic judgments more than human ones in certain domains, especially when accuracy is emphasized. Since the widespread use of generative AI is quite a new phenomenon, however, research has just begun to investigate customers' reactions toward AI and AI-MC in marketing and CRM.

To make a significant and novel contribution to the literature on AI-MC and customer trust, our study aims to delve deeper into the understanding of customers' perceptions of AI-MC in an e-commerce situation, specifically focusing on customer trust, using a realistic CRM scenario. We, therefore, conducted an experimental study varying the sender of an email in a product return context from no AI agency to complete AI agency. We described the email communication with the customer as either written by (a) a service employee, (b) a service employee assisted by AI, or (c) an AI on behalf of the service employee. We further modified the service criticality of the product return scenario by describing either a high-price product urgently needed or a low-price product not urgently demanded. As highlighted by recent AI research, managing AI-driven communications in a way that maintains consumer autonomy and trust is critical for avoiding negative reactions (Spais et al. 2023). By examining the trust components benevolence, integrity, and competence, we gain a deeper understanding of how AI-MC affects customer trust and thus make both theoretical contributions (i.e., by extending the recent literature on how different degrees of AI-MC impacts customer trust, specifically by disentangling trust in its components; Akbar et al. 2024) and practical contributions (e.g., for developing marketing strategies to incorporate AI-MC in CRM effectively). Our research thus provides a novel and significant contribution to the current literature on AI-MC and customer trust, which is of high contemporary relevance, particularly in light of current regulations emphasizing transparency in the use of AI in marketing (European Commission 2024).

2 | Theoretical Background

With the new possibilities of generative AI creating texts, pictures, and audiovisual material, the question arises about how AI-MC affects interpersonal communication and might change the way conversational partners perceive each other. In e-commerce, eliciting and protecting trust, i.e., "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer et al. 1995; 712), is a principal goal, as customer trust is essential for a company's success (Isaeva et al. 2020). However, the rapid proliferation of generative AI along the customer journey (Dencik et al. 2023) is faced with the recent observation that customers often mistrust AI-generated communication (Prakash et al. 2023). Customers may find themselves in a vulnerable position while interacting with AI due to their personal circumstances or the complexities of a particular situation (Mogaji et al. 2020). The perception and use of AI could potentially exacerbate this vulnerability. As noted by Longoni and Cian (2020) AI-MC is more readily trusted when customers view the context as utilitarian, where AI's competence shines, rather than hedonic, where customers may doubt AI's emotional intelligence and nuanced decision-making. While AI is merely a tool with no inherent harmful attributes (Tuffley 2019), its usage in customer service is often segmented based on task complexity. Customers seem to prefer AI for less challenging issues but lean toward human assistance when tasks become more intricate (Xu, Chen, et al. 2020). The preference is driven by customers' belief in the AI's capacity to solve problems (Prakash et al. 2023). However, this can potentially amplify the customer's vulnerability if AI fails to solve complex issues, escalating the perceived risk (Xu, Chen, et al. 2020). Furthermore, AI's growing role in marketing has raised concerns about its potential to undermine customer autonomy. The ability to automate decisions and recommendations without human oversight can sometimes lead to perceptions of control loss, further eroding trust in AI (Spais et al. 2023). In healthcare contexts, for example, customers are often resistant to AI recommendations due to perceived uniqueness neglect—the belief that AI systems cannot account for their individual circumstances (Longoni et al. 2019). These findings reinforce the importance of trust in AI-MC in scenarios where the perception of personal uniqueness is crucial. AI-MC can disappoint customers' expectations of companies and evoke fears of being deceived or manipulated (Jakesch et al. 2019). In line with his, customers can perceive texts written with the aid of AI or by AI as less trustworthy

(Hancock et al. 2020). Taking this a step further, AI's perceived control over the customer, or lack thereof, can also influence a customer's trust in AI agents (Yang et al. 2022). The authors discovered that, while anthropomorphizing AI agents can enhance customers' acceptance in cases where the perceived control is high—it could conversely decrease their acceptance in low control situations—adding yet another source of vulnerability. Jakesch et al. (2019) investigated how using AI to create online profiles of Airbnb hosts influenced trust perceptions of these hosts. Their findings suggest that when profile descriptions of the Airbnb hosts were presented as either all human-written or all AI-generated, participants gave almost identical trust ratings to the profiles matching the pre-rated trust level of the profiles. In a setting where participants suspected host profiles to be AI-generated or labeled as such, however, participants rated these as less trustworthy. The authors refer to this observation as *Replicant Effect* and explain their findings with the *Hyperpersonal Model of CMC* (Walther and Whitty 2021), proposing that over-attributions based on the participants' suspicion that the profile was AI-generated or by the label indicating that a profile was AI-generated accounts for the lower trust ratings. Liu et al. (2022) explored AI-MC in email communications, varying the degree of AI-MC and the interpersonal emphasis of the email communication. They found that participants rated their conversational partner lowest on trustworthiness when AI completely mediated the email communication, while trust perceptions were higher when the conversational partner was aided by AI or used no AI in his e-mail message. Interestingly, this effect occurred independent of the personal emphasis of the communication. Drawing on the described findings, we expect similar results for an e-commerce context and hypothesize:

H1. *Customer trust in an e-com retailer is higher when an online retailer's email is labeled as being written by a service employee than when the email is labeled as being written by a service employee assisted by AI or by AI on behalf of the service employee.*

Trust is a multi-dimensional construct comprising at least three elements: *benevolence, integrity*, and *competence* (McKnight and Chervany 2001). Benevolence refers to the degree of positive orientation of a trustworthy party toward the welfare of the trust beyond selfish gain (Mayer et al. 1995; McKnight and Chervany 2001). Integrity reveals itself in the perception that the trustworthy party adheres to recognized principles and values that align with the trustor's expectations (McKnight and Chervany 2001; Mozafari et al. 2021). Finally, competence relates to the ability of the trustworthy party to perform certain activities satisfactorily (Mozafari et al. 2021; Rofiq and Mula 2009). Recent research elucidates that AI systems often appear highly competent but less benevolent and less integral than their human counterparts, which poses an influence on trust formation (Li and Bitterly 2024; Novozhilova et al. 2024). In some contexts, AI systems are even perceived as more competent than humans, which means that people are more likely to follow the recommendations of AI than of other people (Spais et al. 2023; Zhang et al. 2023). The level of agency accorded to AI can both enhance and diminish trust (Vanneste and Puranam 2021). This prompts the need for a precise consideration of trust components when adopting AI systems in several societal settings (Novozhilova et al. 2024). Thus, acknowledging and understanding customer vulnerability in the blend of human and AI customer service interaction is crucial to ensure the successful management of consumer trust in the realm of AI-MC and consequently in the success of e-commerce businesses (Ameen et al. 2021). Mozafari et al. (2021) found that the loss of trust in chatbots after disclosure in situations of high service criticality was due to lower perceptions of the chatbot's competence and benevolence but not based on lower perceptions of the chatbot's integrity. Moreover, when a customer's service request could not be resolved, chatbot disclosure mitigated the adverse customer reactions so that customer trust was even increased (Mozafari et al. 2021). In particular, customers reacted positively to chatbot disclosure in a failure situation due to firmer beliefs in the chatbot's integrity and benevolence, while competence beliefs were not affected. AI-powered services in shopping have been shown to improve the overall customer experience by increasing trust, convenience, personalization, and relationship engagement while reducing perceived sacrifices (Ameen et al. 2021). However, this also depends on how competently the AI system performs its tasks—AI customer service has been found to be favored for tasks with low service criticality, while human customer service is favored for tasks with high service criticality, suggesting that perceived problem-solving ability plays an important role in mediating customers' usage intentions (Xu, Shieh, et al. 2020). Heider's (1958) attribution theory posits that individuals make sense of their surroundings by attributing cause and effect to people's behaviors and events. In doing so, individuals are tempted to relate the behavior of others to internal factors such as personality traits or abilities (Heider 1958). Recent research showed that conversational partners using AI in interpersonal relationships were not considered to put the same effort into a friendship as they would by personally writing the message, which, in turn, leads to decreased relationship satisfaction and uncertainty for the conversational partner (B. Liu et al. 2023). Accordingly, we argue that in CRM contexts, customers may perceive online retailers as less benevolent and integral if a service employee, representing the retailer, partly or completely uses AI to engage with the customer, as the use of AI may imply diminished effort from the service employee in communication compared to manual drafting (Prentice and Nguyen 2020). We thus hypothesize:

H2. *Customers' perceptions of benevolence and integrity are higher when an online retailer's email is labeled as being written by a service employee than when the email is labeled as being written by a service employee assisted by AI or by AI on behalf of the service employee.*

Since trust enables individuals to accept perceived vulnerability (Mayer et al. 1995), customer trust seems to be especially relevant in customer situations of high service criticality, that is, when the outcome of a service situation particularly matters to customers (Crisafulli and Singh 2017). Mozafari et al. (2021) showed that in an AI-Chatbot environment, service criticality moderated the trust–AI relationship across two separate experiments. In situations of high service criticality, participants trusted less in a conversational partner when this partner disclosed herself as a chatbot at the end of the conversation compared to a non-disclosure scenario. However, chatbot disclosure did not affect customer ratings in a situation of low service criticality but in a situation of high service criticality. In contrast, when the chatbot could not solve the customer's service request, chatbot disclosure enhanced customer trust. It mitigated the effects of the negative service outcome as compared to when the chatbot was not disclosed. In line with these findings, we expect service criticality to moderate the relationship between AI condition and customer trust, especially in situations where service employee communication is partially or fully mediated by AI. More specifically, we suggest that in situations of high service criticality, the different amounts of AI in a communication will lead to larger differences in customer trust than those of low service criticality. We thus hypothesize:

H3. *Service criticality moderates the relationship between AI-MC and customer trust in an online retailer, such that the difference in customer trust between AI-MC conditions is more pronounced when service criticality is high compared to when service criticality is low.*

3 | Materials & Methods

3.1 | Design and Procedure

We conducted an online experiment to investigate how different degrees of AI-MC affected customer trust in an online retailer and how much this relationship differs between high and low service criticality scenarios. The experiment followed a 3 (degree of AI-MC: email communication written by service employee vs. written by service employee assisted by AI vs. written by AI on behalf of the service employee) ×2 (service criticality: high vs. low) between-subjects design. To reduce demand effects and to conceal the purpose of our study, the consent form briefed participants that the study aimed to explore their perceptions and reactions to email communication from an online retailer. Participants were assigned randomly to an experimental condition and presented with an introductory text and a screenshot of an email exchange with an online retailer. They were instructed to put themselves in the customer's shoes, visualizing the outlined scenario. Next, participants were asked to evaluate their trust in the online retailer. Trust ratings served as dependent variables. Participants were then asked to indicate their perceptions of service criticality and realism of the scenario as a manipulation and validity check, respectively. On the following pages of the questionnaire, data on the participants' dispositional trust and attitude toward AI were collected as control variables, as well as demographic information (gender, age, highest level of education, current vocational status, field of study/profession). Before the end of the questionnaire, participants were asked to indicate how the email communication presented had been written as an attention check. The attention check additionally ensured that the respondents understood whether the email was written by a service employee, an AI, or both. Finally, participants were fully debriefed about the study's objectives and thanked for participating.

3.2 | Participants

Participants were recruited via a university distribution list and various social media platforms. A total of $N = 494$ participants completed the study. However, $N = 200$ had to be excluded as they failed the attention check at the end of the questionnaire by not correctly identifying the experimental condition they were assigned to (see Section 3.4 for the attention check item). The final sample comprised $N = 294$ German-speaking participants, of whom 60.20% identified themselves as female, 37.76% as male, and 2.04% as diverse. The average age of participants was $M = 27.14$ years (SD = 12.08). Most participants were highly educated, holding a university entrance certificate (63.27%), a bachelor's degree/pre-diploma (11.56%), a vocational training/apprenticeship (9.52%), or a master's degree/diploma (7.48%). Most of them indicated that they were currently enrolled in a study program (61.22%), followed by employees (28.23%) and freelancers (3.06%).

3.3 | Materials

For our experiment, we crafted six different email communications. To vary the degree of AI-MC, we used an approach similar to Liu et al. (2022). Our manipulation of service criticality followed a common scenario technique (see below; Mozafari et al. 2021; Ostrom and Iacobucci 1995; Webster and Sundaram 1998). The designed stimulus material showed an email communication involving a defective product in the context of a product return scenario from an online retailer and was designed by the research team based on the study design by Liu et al. (2022). The product return scenario was selected for its relevance and realism, mirroring real-world customer experiences (see also Huang and Dootson 2022). Given its prominence in online shopping, we chose to situate our scenario within the customer electronics sector (Lohmeier 2024; Statista Market Insights 2024).

The six designed email scenarios illustrated a service employee's response to a customer's return request. Each email acknowledged the customer's request, expressed apologies for the inconvenience due to the faulty item, and assured prompt refund arrangement by the customer service. The email concluded with a request for the customer to follow a provided link to complete the return process and submit personal data for the return process (see Appendix A for the stimulus material). To manipulate the degree of AI-MC, after the regards of the service employee, a sentence in asterisks was included indicating the sender of the email. For the condition in which the service employee wrote the email (complete human agency condition), we added the sentence “This email was personally written by the service employee” for the condition in which the service employee used AI to write the communication (shared human/AI agency condition) we added the sentence “This email was written by the service employee using an intelligent autocomplete system (artificial intelligence).”, and for the condition in which the AI wrote the email on behalf of the service employee (complete AI agency condition), we included the sentence “This email was written by an advanced AI (artificial intelligence) system on behalf of the service employee.”

To manipulate service criticality, participants were asked to read a short scenario before reading the email communication. For the high service criticality condition, participants were asked to imagine having recently purchased a new and costly laptop from an online retailer. Upon its first use, they discovered that the computer was defective in a particularly distressing situation of urgent need for the laptop to complete a crucial student assignment or to prepare a vital job presentation. In the low service criticality condition, participants were asked to envision having recently acquired a low-priced USB charging cable on sale, which they found defective upon first use. However, this situation was framed as less critical, given the non-urgent nature of the need for the cable, as they had other charging cables available for use.

Except for the defective product type and the sentence indicating the degree of AI-MC, the content and wording across the emails remained identical. To improve realism, each email was presented as a screenshot from Gmail, a widely used email client (Petrosyan 2024; Rabe 2024). As a name for the service employee, *Alex Schneider* was chosen as both the given name and the surname are among the most common names in Germany (Wikipedia 2024; Rüdebusch n.d.). For a pre-test of the stimulus material, see the Supporting Information.

3.4 | Measures

Trust in the online retailer was measured with an established questionnaire assessing trust in e-commerce (McKnight et al. 2002). The questionnaire measures trust on the components of benevolence (e.g., "I believe that the online retailer would act in my best interest."; $\alpha = 0.80$), integrity (e.g., "The online retailer is truthful in its dealings with me."; $\alpha = 0.83$), and competence (e.g., "The online retailer is competent and effective in providing electronic products."; $\alpha = 0.81$). The internal consistency of the aggregate trust measure was $\alpha = 0.90$. In line with McKnight et al. (2002), trust was additionally assessed as a behavioral intention with items asking participants to indicate their willingness to engage in trust-related behaviors, such as sharing sensitive personal information (Currall and Judge 1995; McKnight et al. 2002) with the online retailer in the context of this email communication. The three items we used were as follows: "I would click on the link in the email.", "I would provide my contact details (name and address) on the linked website.", and "I would provide my bank details (IBAN) on the linked website." As previous work has produced mixed findings regarding the influence of general trust and attitude toward AI when investigating trust in AI-MC and in AI (Chua et al. 2023; Liu et al. 2022), disposition to trust was additionally measured with the items of McKnight et al. (2002; e.g., "In general, people do care about the well-being of others.", "In general, most folks keep their promises."; $\alpha = 0.89$.). Attitude toward AI was assessed with the German version of the Attitude Towards Artificial Intelligence scale (ATAI scale; Sindermann et al. 2021). This short measure captures attitude toward AI with five items (e.g., "Artificial intelligence will benefit humankind.", "Artificial intelligence will cause many job losses.", $\alpha = 0.81$). As a manipulation and validity check, participants were asked to indicate perceived service criticality ("The fastest possible resolution of my service request is critical to me."; Mozafari et al. 2021), and realism ("This scenario is realistic.") of the presented scenario, respectively. As an attention check, participants were asked to indicate how the presented email communication was written ("Who wrote the online retailer's email?"). The attention check further helped to ensure that respondents understood correctly whether the email had been written by a service employee, a service employee with the help of an AI or by an AI on behalf of a service employee depending on their respective experimental condition. Response options were identical to the wording used in the experimental manipulation ("This email was personally written by the service employee" vs. "This email was written by the service employee using an intelligent autocomplete system (artificial intelligence)" versus "This email was sent by an advanced AI (artificial intelligence) system on behalf of the service employee."). All measures of the study were assessed using 7-point Likert-type scales (1 = *strongly disagree* to 7 = *strongly agree*).

4 | Results

4.1 | Data Preparation

The average percentage of missing data across all recorded variables was 1.80%. These missing data were replaced with median (continuous variables) and mode values (categorical variables).

4.2 | Statistical Analyses

ANOVA and ANCOVA analyses were conducted with type III SS, as experimental conditions yielded unbalanced sample sizes (Hector et al. 2010; Shaw and Mitchell-Olds 1993; see Table 1). To further examine significant main effects within ANCOVA, Tukey post hoc tests on the estimated marginal means (EMMs) of the different experimental conditions were calculated. Accordingly, for group comparisons, EMMs and SE are reported (H1–H3). Effect sizes are reported in line with Cohen (1998).

4.3 | Manipulation and Validity Checks

Two-way ANOVAs were performed to evaluate the effects of AI-MC condition, service criticality, and their interaction on perceived service criticality (manipulation check) and realism (validity check). For perceptions of service criticality, results yielded a significant main effect of service criticality, $F(1, 288) = 6.53$, $p = 0.011$, $\eta_p^2 = 0.02$, while the main effect of AI-MC condition and the interaction term were non-significant ($ps \geq 0.474$). We thus further investigated perceptions of service criticality among the high and low service criticality conditions. An independent sample Welch's t-test revealed that in the high

TABLE 1 | Sample sizes across experimental conditions.

	AI-MC		
Service criticality	**Service employee**	**Service employee assisted by AI**	**AI on behalf of service employee**
High	25	55	74
Low	19	52	69

Note: Total $N = 294$.
Abbreviations: AI-MC, artificial intelligence-mediated communication; AI, articicial intelligence.

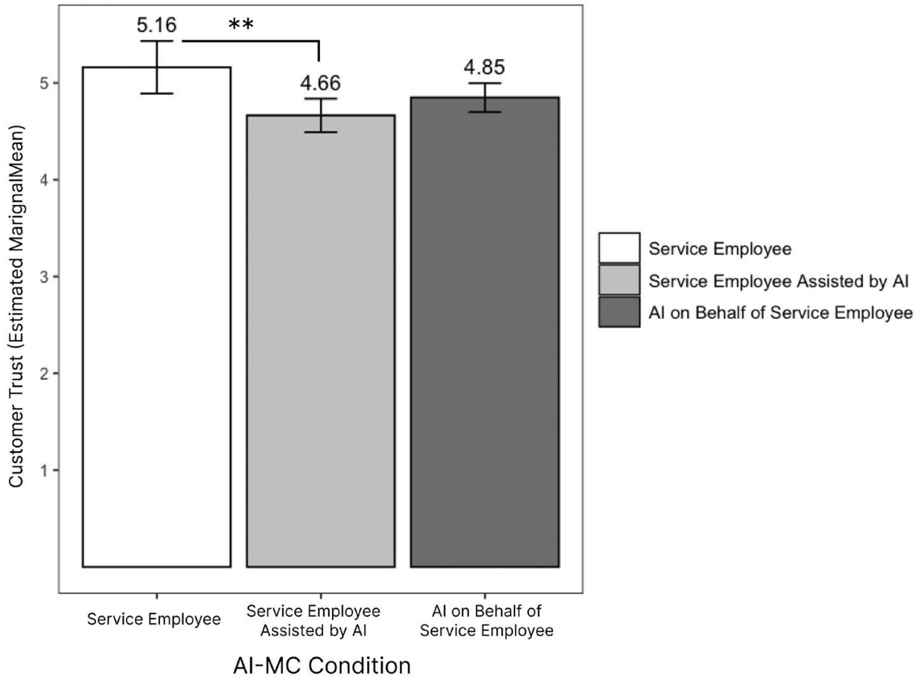

FIGURE 1 | Customer trust ratings across AI-MC conditions (H1). The float values above each bar represent the trust score (EMM); the vertical black lines indicate the 95% confidence intervals of the SE. Lines with asterisks indicate significant differences between groups based on adjusted *p*-values (Tukey post hoc tests; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$, two-tailed).

service criticality condition, participants reported higher perceptions of criticality regarding the resolution of their service request ($M=6.45$, SD $=0.96$) than in the low service criticality condition ($M=6.16$, SD $=1.03$, t $(284.82)=2.50$, $p=0.014$, $d=0.29$ [0.06; 0.52]). For perceived realism, there were no significant main effects or interaction ($ps \geq 0.439$), suggesting that participants' perception of realism did not differ across the six experimental conditions. A follow-up one-sample t-test against the mid-point of the scale (i.e., 4) indicated that participants perceived the product return scenarios and email communications as highly realistic ($M=5.49$, SD $=1.30$, t $(293)=19.64$, $p<0.001$, $d=1.15$ [1.00, 1.29]).

4.4 | Effects of AI-MC on Customer Trust (H1)

To test H1, we conducted a one-way ANCOVA to determine whether customer trust ratings significantly differed between the three AI-MC conditions. Mean customer trust ratings served as the dependent variable, while age, gender, disposition to trust, and the attitude toward AI were entered as covariates. In line with H1, the main effect of AI-MC condition proved significant, $F(2, 286)=4.65$, $p=0.010$, $\eta_p^2=0.03$. Regarding the covariates, disposition to trust was significantly related to customer trust ratings, $F(1, 286)=11.08$, $p<0.001$, $\eta_p^2=0.04$, while other covariates were non-significant ($ps \geq 0.526$). Tukey post hoc tests revealed that the covariate adjusted mean of customer trust ratings was significantly greater in the complete human agency condition (EMM $=5.16$, SE $=0.14$) than in the shared human/AI agency condition (EMM $=4.66$, SE $=0.09$, t $(291)=3.03$, $p=0.007$, $d=0.54$ [0.185, 0.90]), indicating a moderate effect. Group differences between the complete human agency condition and the complete AI agency condition (EMM $=4.84$, SE $=0.08$) as well as between the shared human/AI agency and the complete AI agency condition failed to reach significance ($ps \geq 0.118$). Figure 1 illustrates the EMMs for customer trust ratings across AI-MC conditions along with the SE, 95% CI, and significant group differences.

As an additional test of H1, we conducted the same statistical analyses as reported above with the behavioral intention trust measures as dependent variables across AI-MC conditions. The main effect of AI-MC condition was non-significant for all three behavioral intention trust measures ($ps \geq 0.167$). In terms of the covariates, age and disposition to trust were significantly related to the participants' willingness to click on the link in the online retailer's email (age: $F(1, 286)=6.12$, $p=0.014$, $\eta_p^2=0.02$; disposition to trust: $F(1, 286)=6.30$, $p=0.013$, $\eta_p^2=0.02$), to share their name and address with the online retailer (age: $F(1, 286)=8.46$, $p=0.004$, $\eta_p^2=0.02$; disposition to trust: $F(1, 286)=6.26$, $p=0.013$, $\eta_p^2=0.02$), and to share information on their bank account with the online retailer (age: $F(1, 286)=4.68$, $p=0.031$, $\eta_p^2=0.02$; disposition to trust: $F(1, 286)=10.07$, $p=0.002$, $\eta_p^2=0.03$). Other covariates were not significantly related to the behavioral trust measure ($ps \geq 0.053$). See Figure 2 for the EMMs and SE with the 95% CI of the behavioral intention trust measures across AI-MC conditions.

Given these findings, H1 proposing that customer trust in an e-commerce retailer is higher when the e-commerce retailer's email is labeled as being sent by a service employee compared to when the email is labeled as being sent by a service employee assisted by AI or by AI on behalf of the service employee could be partly accepted (see discussion for the interpretation of non-significant finding of the difference between the complete human and the complete AI agency conditions and the behavioral intention trust measures, see Table 2 for a summary of the study results).

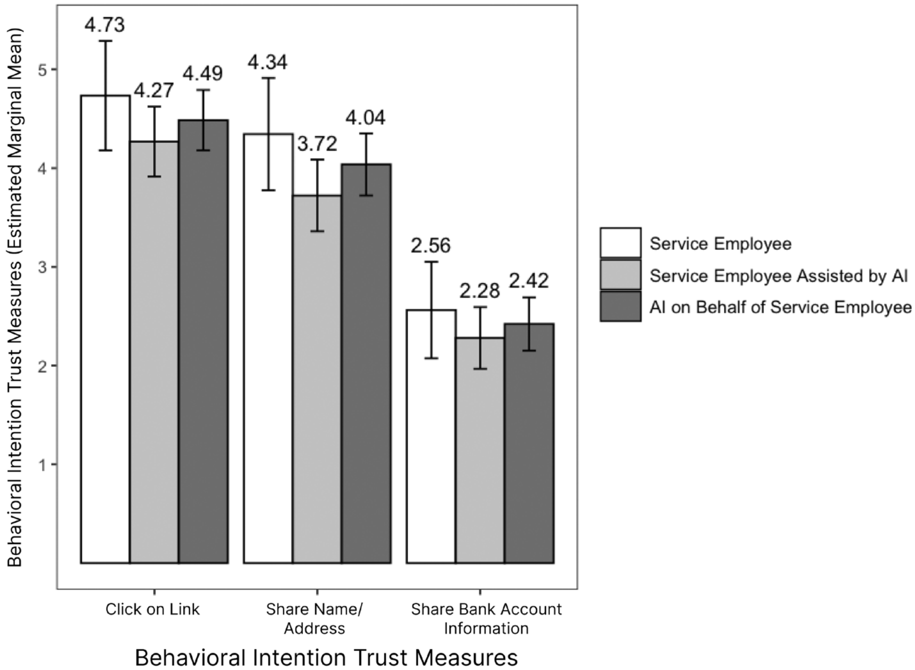

FIGURE 2 | Behavioral intention trust measures across AI-MC conditions (H1). The float values above each bar represent the trust score (EMM); the vertical black lines indicate the 95% confidence intervals of the SE.

4.5 | Effects of AI-MC on the Trust Components Benevolence, Integrity, Competence (H2)

To test H2, the same statistical analyses as described for H1 were conducted with perceptions of the trust components benevolence, integrity, and competence as dependent variables. Analyses showed a significant main effect of AI-MC condition on perception of the online retailer's benevolence, $F(2, 286)=4.59$, $p=0.011$, $\eta_p^2=0.03$, integrity, $F(2, 286)=4.02$, $p=0.019$, $\eta_p^2=0.03$, and competence, $F(2, 286)=3.16$, $p=0.044$, $\eta_p^2=0.02$. In terms of the covariates, disposition to trust yielded significant relationships with all trust components (benevolence: $F(1, 286)=9.53$, $p=0.002$, $\eta_p^2=0.03$; integrity: $F(1, 286)=8.09$, $p=0.005$, $\eta_p^2=0.03$; competence: $F(1, 286)=7.70$, $p=0.006$, $\eta_p^2=0.03$). Other covariates were non-significant ($ps \geq 0.153$).

Tukey post hoc group comparisons on the covariate adjusted means revealed that in the complete human agency condition, participants perceived the online retailer as more benevolent and integral than in the shared human/AI agency condition (benevolence: $EMM_{complete\ human\ agency}=5.15$, $SE=0.18$ vs. $EMM_{shared human/AI agency}=4.49$, $SE=0.12$, $t(291)=3.03$, $p=0.007$, $d=0.54$ [0.19, 0.90]; integrity: $EMM_{complete\ human\ agency}=5.50$, $SE=0.15$; $EMM_{shared\ human/AI\ agency}=5.01$, $SE=0.10$, $t(291)=2.78$, $p=0.015$, $d=0.50$ [0.14, 0.86]), suggesting moderate effect sizes. Further, participants rated the online retailer higher on integrity in the complete human agency condition as compared to the complete AI agency condition ($EMM=5.09$, $SE=0.08$, $t(291)=2.42$, $p=0.041$, $d=0.42$ [0.08, 0.76]), indicating a small effect size, while differences between the complete human agency and the complete AI agency condition were non-significant for benevolence ratings ($p=0.088$). Comparisons of perceptions of benevolence and integrity between the complete AI agency and the shared human/AI agency condition proved to be non-significant ($ps \geq 0.337$). Although a significant main effect of AI-MC was observed for competence perceptions, Tukey post hoc comparisons did not reveal significant differences between the conditions ($ps \geq 0.084$). Figure 3 shows the EMMs for benevolence, integrity, and competence across the AI-MC conditions, with the SE, 95% CI, and significant group comparisons.

Given these findings, H2 stating that customers' perception of benevolence and integrity is higher when the e-commerce retailer's email is labeled as being sent by a service employee compared to when the email is labeled as being sent by a service employee assisted by AI or by AI on behalf of the service employee could be largely accepted (see Table 2 for a summary of the study results).

4.6 | Moderating Effect of Service Criticality on the Relationship Between AI-MC and Customer Trust (H3)

To test H3, proposing that service criticality moderates the relationship between AI-MC and customer trust such that in situations of high service criticality, the difference in trust ratings is more pronounced between the AI-MC conditions compared to situations of low service criticality, we conducted ANCOVAs with the two between-subjects factors of AI-MC condition and service criticality including their interaction term. Mean customer trust ratings, behavioral intention trust measures, and trust components served as dependent variables; age, gender, disposition to trust, and attitude toward AI were entered as covariates. ANCOVAs revealed no significant interaction between AI-MC condition and service criticality for any of the trust measures (i.e., customer trust ratings, behavioral intention trust measures, trust components; $ps \geq 0.559$). Similarly, the main effects of service criticality were non-significant for any of the trust measures ($ps \geq 0.090$). The main effects of AI-MC and the relationships between the covariates and the trust measures were consistent with previously reported results (see Sections 4.4 and 4.5). Thus, H3, proposing that service criticality moderates the relationship between AI-MC and trust, was rejected, suggesting that the perceived criticality of service situations did not influence the effects of AI-MC on trust as hypothesized (see Table 2 for a summary of the study results).

5 | Discussion

5.1 | Theoretical Contributions

With the widespread accessibility of generative AI, such as ChatGPT, companies have started implementing this new technology in their workflows to realize cost savings and increase efficiency. Specifically, for marketing and CRM, generative AI appears to be promising (Chui et al. 2023). Applying generative AI to facilitate CRM, however, raises the question of how customers react to it and how AI and customer communication mediated by AI influence customer trust – a prerequisite for a company's business success (Isaeva et al. 2020). With the EU AI Act, which came into force on 1 August 2024, companies in Europe are obliged to make the use of AI transparent to customers (European Commission 2024) so that understanding customers' reactions toward the use of AI labeled as this is essential. To address this research gap, the present research aimed to unveil how different degrees of AI-MC, covering the spectrum of complete human agency to complete AI agency, affect customer trust in an online retailer, thereby extending previous work on AI-MC and trust in personal relationships (e.g., Hohenstein and Jung 2020; Liu et al. 2022, 2023) and online self-presentation (Jakesch et al. 2019). To gain a deeper understanding of the dynamics between AI-MC and customer trust, this study disentangled customer trust in its components integrity, benevolence, and competence and explored how perceptions of these trust components are specifically affected when an online retailer uses AI-MC in customer communication. By examining the trust components, this research adds to the literature on trust and AI-MC, as most studies have focused on the exploration of AI-MC and trust on an aggregate trust level (e.g., Dehghanpouri et al. 2020; Hohenstein and Jung 2020; Jakesch et al. 2019; Liu et al. 2022, 2023; Longoni and Cian 2020). An additional goal of this research was to explore the role of service criticality in the relationship between different degrees of AI-MC and customer trust, expanding former research which examined how human-chatbot interactions (i.e., complete AI agency) impact customer trust in service frontline settings (Mozafari et al. 2021).

On an aggregate trust level, the results of our research indicate that individuals are more likely to trust an online retailer when the CRM communication is labeled as written by

TABLE 2 | Summary of the study results.

Hypothesis	Result	Key finding
H1: Customer trust in an e-com retailer is higher when an online retailer's email is labeled as being written by a service employee than when the email is labeled as being written by a service employee assisted by AI or by AI on behalf of the service employee.	Partially supported	• Participants reported higher trust in the online retailer when the email was labeled as written by a service employee compared to when it was labeled as written by a service employee assisted by AI (moderate effect). • Trust did not significantly differ between emails labeled as written by a service employee and those labeled as written by AI on behalf of the service employee.
H2: Customers' perceptions of benevolence and integrity are higher when an online retailer's email is labeled as being written by a service employee than when the email is labeled as being written by a service employee assisted by AI or by AI on behalf of the service employee.	Largely supported	• Participants reported higher perceptions of the online retailer's benevolence and integrity when the email was labeled as written by a service employee compared to when it was labeled as written by a service employee assisted by AI (moderate effect). • Participants reported higher perceptions of the online retailer's integrity when the email was labeled as written by a service employee rather than by AI on behalf of the service employee (small effect). • Benevolence perceptions of the online retailer did not significantly differ between emails labeled as written by a service employee and those labeled as written by AI on behalf of the service employee.
H3: Service criticality moderates the relationship between AI-MC and customer trust in an online retailer, such that the difference in customer trust between AI-MC conditions is more pronounced when service criticality is high compared to when service criticality is low.	Not supported	• The level of service criticality did not significantly influence customer trust levels for different AI-MC degrees.

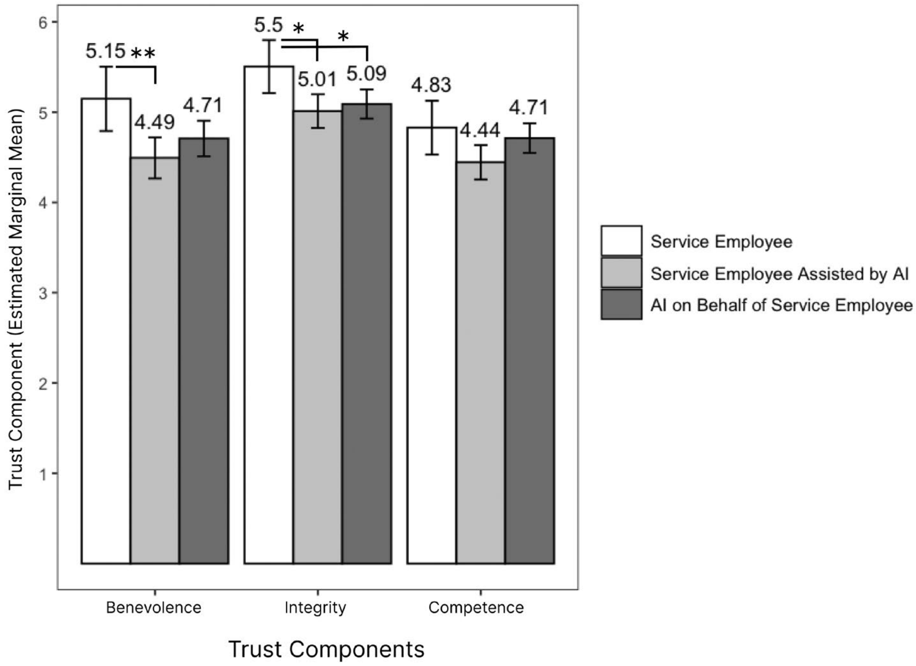

FIGURE 3 | Ratings of trust components over AI-MC condition (H2). The float values above each bar represent the trust score (EMM); the vertical black lines indicate the 95% confidence intervals of the SE. Lines with asterisks indicate significant differences between groups based on adjusted p-values (Tukey post hoc tests; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$, two-tailed).

a service employee compared to when the CRM communication is described as written by a service employee assisted by AI (see Table 2). These results fit with previous research by Liu et al. (2022) who found that participants' trust in email writers decreased when participants learned that the email was written by a person using AI. It also aligns with Hancock et al. (2020) who postulate that AI-generated content is perceived as less trustworthy. Thus, content created with the help of AI and labeled as such can hurt customer trust in an online retailer. These findings can be interpreted in the context of *AI avoidance* (Erlei et al. 2022) and human prejudice toward AI (Meikle and Bonner 2024). In line with this, the lower trust ratings for the shared human/AI agency condition may reflect a tendency of individuals to avoid AI systems, particularly in domains that are perceived as human and thus require human qualities like empathy or emotional intelligence (Longoni et al. 2019). A possible explanation could be that this avoidance is particularly pronounced in situations where the extent of AI influence is ambiguous or uncertain (Buder et al. 2024). Our results suggest that mentioning AI involvement in customer communication might trigger this avoidance response, which is manifested in lower trust ratings. Our results also align with research on AI avoidance in consumer contexts. For instance, Meikle and Bonner (2024) found that people tend to underestimate AI capabilities due to exponential growth bias and reject the aversive implications of rapid technological progress due to motivated reasoning. This could explain why participants showed lower trust in the shared human/AI agency condition, despite the potential benefits of AI in customer service. The avoidance of AI observed in this study may be rooted in similar cognitive biases, where participants are motivated to maintain a belief in human superiority in customer service contexts (Meikle and Bonner 2024). Individual differences in trust baselines, however, may also modulate AI acceptance. In a recent study, Molina and Sundar (2024) found that users apply either a positive or negative machine heuristic—seeing machines as either more accurate or lacking nuance—depending on factors such as their trust in humans, fear of AI, power usage, and political orientation. This finding suggests that trust in AI might not only be a function of perceived competence or transparency but also reflect underlying attitudes toward human fallibility.

Interestingly and at odds with former research (Liu et al. 2022), no significant difference in customer trust on an aggregate trust level was found between CRM communications labeled as written by a service employee and those labeled as written by an AI on behalf of the service employee (see Table 2). This finding is particularly noteworthy as it challenges the assumption that complete AI agency would necessarily diminish trust more than AI-assisted communication (Liu et al. 2022). One possible explanation for the more positive perception of complete AI agency could be its high perceived competence in specific domains. Prior research supports this interpretation, demonstrating that individuals may exhibit *algorithm appreciation* (Logg et al. 2019) when AI is regarded as competent and capable of making accurate decisions. The notably low trust evaluation of the shared human/AI agency condition may suggest that this scenario combines the disadvantages of both alternatives, leading to a more negative assessment, as this scenario combines the potential errors and subjective biases of human judgment with the lack of transparency and explainability of AI-based decisions. As content entirely generated by AI becomes increasingly normalized in digital interactions, customers may no longer react as negatively to completely AI-mediated responses in e-commerce, particularly when efficiency is perceived as a desirable service attribute (Novozhilova et al. 2024). This underscores the importance of framing AI-MC in e-commerce: if AI is perceived as an autonomous decision-making agent integrated into the company's processes—rather than as an intrusive or uncertain factor—it may not provoke strong trust-related concerns. Similar dynamics have been observed in the hospitality and tourism sector, where customers' prior experience with AI, trust perceptions, and engagement with electronic word-of-mouth (eWOM) significantly influence their intention to use AI-enabled services (Alam et al. 2024). These findings support the idea that user familiarity and positive framing of AI applications can mitigate initial trust concerns in service interactions. In line with this, the observed lack of difference in trust between the complete human and complete AI agency conditions contributes to the growing literature suggesting that customers become more accepting of AI in consumer interactions, which might be especially the case when it is presented as a seamless part of the service rather than as a supplementary aid. A further explanation for this interesting finding could be the *Replicant Effect*, which postulates that trust particularly decreases when individuals do not know if a whole text or which part of a text is produced by a human or an AI (Jakesch et al. 2019). Jakesch and colleagues argue that this distrust stems from a feeling of resentment toward AI-generated content, as they found that participants perceive its use as lazy or inauthentic and content created with AI as less emotional in the context of Airbnb hosts' online self-presentation. Perceptions like these might explain the decrease in customer trust we observed in our study when CRM communication was labeled as written by a service employee assisted by AI, as it remained unclear which specific parts were created by the employee and which by the AI.

Disentangling trust in its components, our analyses further reveal that the observed differences in customer trust ratings across the AI-MC conditions are rather due to lower perceptions of the online retailer's benevolence, particularly in the shared human/AI agency condition, and integrity, in both the shared human/AI agency and the complete AI agency condition, than differences in perceptions of the online retailer's competence (see Table 2). This finding aligns with recent research by Li and Bitterly (2024) as well as Novozhilova et al. (2024), who showed that AI systems are often perceived as less trustworthy, particularly in terms of benevolence and integrity. Our study extends these findings by demonstrating that also in customer service contexts, AI involvement can negatively impact perceptions of these trust components. Our findings are also partly in line with Mozafari et al. (2021) who showed that in a customer interaction participants rate a chatbot lower on competence and benevolence after the chatbot discloses itself as such. Mozafari et al. (2021) suggest that chatbots and AI systems, despite providing identical answers, might be perceived as less knowledgeable than humans. Moreover, it appears that less empathy is attributed to AI, which is reflected in a diminished perception of benevolence (Bhattacherjee 2002). The low ratings in benevolence and integrity observed in the shared human/AI agency condition might indicate that the customers' expectations of the company's benevolence and integrity were not met (Jakesch et al. 2019), thus affecting customer trust more profoundly than if purely AI was used. Interestingly and in line with our findings on an aggregate trust level, the differences in benevolence perceptions were found between the complete human and shared human/AI agency conditions, but not between the complete human and the complete AI agency conditions. This suggests that the perceived benevolence, which is typically attributed to human interactions, was violated by the partial use of AI by the service employee. Again, this aligns with the *Replicant Effect* which suggests that a lack of transparency about the creator of a text (human vs. AI) leads to decreased trust levels (Jakesch et al. 2019).

Our study does not confirm a moderating role of service criticality in the relationship between customer trust and AI-MC, as the differences in customer trust ratings across the AI-MC conditions were not significantly affected by high or low service criticality (see Table 2). This diverges from previous research which revealed service criticality as a moderator and found that especially in high service criticality situations, participants' trust in a chatbot decreases after its disclosure (Mozafari et al. 2021). One explanation for this incongruency could be that our manipulation of service criticality was not strong enough to elicit meaningful differences between the conditions. We neither found an effect of AI-MC trust when measured as behavioral intentions; that is, the participants' willingness to make themselves dependable on and vulnerable to the online retailer by clicking on a link in the email and providing the retailer with sensitive personal data. This is surprising and at odds with former work showing that trust precedes trusting intentions, which, in turn, leads to trust-related behaviors (McKnight et al. 2002). To address this issue, future research could use more established measures to capture trusting intentions.

The lack of an effect on behavioral intentions despite differences in trust ratings may indicate a dissociation between explicit attitudes toward AI (as measured by trust ratings) and implicit behaviors. This dissociation has been observed in other domains of AI interaction (Logg et al. 2019) and may suggest that while people explicitly express lower trust in AI-mediated communications, their actual behaviors may not always align with these expressed attitudes. This phenomenon warrants further investigation and may have implications for how businesses implement AI in customer-facing roles.

5.2 | Practical Implications

For practitioners, our research holds many interesting findings and implications. First, we find that using AI-MC in customer communications and labeling it as such leads to lower customer trust ratings in the online retailer, indicating a moderate effect. This effect appears to be exceptionally prominent for customer communications labeled as written by the service employee assisted by AI; however, when the CRM communication was described as entirely written by an AI on behalf of the service employee, decreases in trust specifically pertained to perceptions of the online retailer's integrity. This is an interesting insight for companies discussing how to successfully implement AI for workflow efficiency in CRM. In particular, with the new EU AI Act, companies in Europe are obliged to make the usage of AI transparent (European Commission 2024) so it is likely that in customer communications, companies will have to label whether a CRM communication has been either written with the help of AI or entirely by AI on behalf of their employees. Thus, practitioners may weigh the pros and cons of using AI-MC in customer communication regarding its potential impact on customer trust in the company.

Interestingly, communication created entirely by AI partly achieved higher trust ratings than content created by a human assisted by AI. This observation is contrary to the currently common practice in the field known as the *Human-in-the-loop* approach, which refers to using AI in various customer concerns, with a human involved to ensure the quality of content generation (Zanzotto 2019). Based on the results of our study, it would be reasonable to assume that minor customer concerns or service inquiries following standard procedures, particularly those with low service criticality, might be automated and handled solely by AI. However, when customer concerns become more complex, it might be necessary to escalate them to a service employee. This finding challenges the assumption that adding human oversight to AI systems will always increase customer trust. It suggests that in some cases, a fully automated AI system, which is explicitly labeled as such, might be preferable to a hybrid human/AI approach, at least in terms of customer trust. This idea resonates with findings from professional collaboration settings. In a recent study, Nkembuh (2025) demonstrated that AI-MC can both facilitate and hinder trust formation and negotiation outcomes depending on perceived agency and contextual clarity. Particularly, in remote, task-oriented interactions, AI's role as a neutral and structured communicator was sometimes preferred over human-led ambiguity. Companies might thus consider clearly delineating AI and human roles in customer communications, rather than blending them in ways that might create intransparency, uncertainty, or discomfort for customers.

Finally, building on the findings of this research, companies might mitigate decreases in customer trust by targeting specific trust components. For example, they might enhance benevolence by emphasizing human oversight in sensitive scenarios, improve integrity through transparent communication about AI fairness, and bolster competence by showcasing AI reliability and accuracy. Tailored interventions like these could help repair trust deficits and strengthen customer relationships in AI-mediated interactions.

5.3 | Limitations and Future Research

Our research holds several limitations. We explored the impact of AI-MC on customer trust in an online retail scenario involving the return of consumer electronics. This specific focus limits the extent to which our findings may be applicable to other product segments (e.g., fashion or food) or business models (e.g., Business-to-Business or Direct-to-Consumer). Therefore, it necessitates further research to understand the effects of AI-MC within these diverse online retail contexts. To further enhance the generalizability of our results, examining the AI-MC and customer trust relationship in different contexts, such as complaint management, product inquiries, order updates, maintenance, and service reminders or claims, would be beneficial. Our findings, revealing lower trust ratings in the shared human/AI and complete AI agency conditions, resonate with those of Jakesch et al. (2019), yet partly contradict Liu et al.'s (2022) research, which found that decreases in trust were lowest when the communication was entirely written by an AI on behalf of a person. Hence, this apparent discrepancy underscores the necessity for future research to further probe the complex dynamics of customer trust in varying human and AI agency conditions. Participants showed higher trust in the online retailer when CRM communication was labeled as written by a service employee, while trust decreased significantly when AI was involved, particularly in the shared human/AI condition. Notably, CRM communication entirely written by AI further reduced perceptions of the retailer's integrity. Future studies should further investigate whether our results can be applied to other customer branches, such as banking, insurance, health care, or AI-enabled consulting, where procedures might be less standardized, and customers might be even more dependable and vulnerable to the company, as in the case of an accident or illness. In line with this, AI-MC can offer additional opportunities and risks, especially in industries with high individually perceived vulnerability, such as the financial sector. It would thus be particularly interesting to examine how AI-MC can support processing insurance claims or inquiries to financial service providers without weakening customer trust in the insurance.

Further research on the long-term effects of AI-MC is essential for understanding the sustainability of its impact on customer trust. Such studies could determine whether trust developed or reduced through AI-MC endures over time, providing valuable insights into the lasting influence of AI on consumer relationships (Li et al. 2023). Additionally, future studies should explore the impact of AI-MC on trust within internal communications, including interactions between employees and between employees and the organization, alongside the external communication context (Balan and Sritharan 2024).

In addition, our study may hold potential limitations due to the research method we chose, which should be addressed. This research was carried out in the context of an undergraduate student's course, and a university distribution list, as well as social networks, were primarily used to recruit participants. Consequently, most of the participants indicated they were highly educated, and more than half were students, followed by slightly more than a quarter of employees. In addition, our study was aimed at German-speaking participants. Thus, although our study was carried out as an anonymous online experiment, implicit response biases or perceived coercion of the participants cannot be ruled out completely, nor can the influence of cultural factors be excluded. Hence, the results we obtained may not be generalized to other countries and cultures and should be interpreted with consideration of the recruited sample (Paul 2024). Therefore, to further validate the effects we found, this experiment should be repeated with a more representative sample, including a larger part of employees and participants from other countries, for example. In addition, a significant number of participants failed the attention check we implemented and did not correctly identify the experimental condition, leading to uneven group distribution and smaller sample sizes in some experimental conditions. This may be attributed to the participants' selective attention, which is a common challenge in online research (Rodd 2024). To mitigate this limitation, we employed a comprehension question as the attention check, asking participants to identify their assigned experimental condition rather than directly asking if they understood the scenario. This approach reduced the potential for social desirability bias (Pei et al. 2020), ensuring that only those who were fully attentive and aware of their condition were included in the final analysis. We addressed the resulting imbalance in sample sizes across the experimental conditions using appropriate statistical methods; however, it remains a limitation of our study that should be acknowledged.

Finally, we did not find an effect of service criticality on AI-MC and customer trust, which might be because our experimental manipulation was not strong enough. Thus, our finding that service criticality does not moderate the relationship between AI-MC and customer trust should be taken preliminarily. As theory and practice are highly interested in understanding whether service criticality impacts customer trust across levels of AI-MC, future studies should follow this track and apply stronger manipulations of service criticality. One possibility to enhance the strength of the manipulation could be to use even more expensive and valuable products, such as a car versus a car accessory, for example. It is also possible to create a scenario involving a critical service, for example, services for an upcoming wedding party or anniversary, which cannot be delayed (Ostrom and Iacobucci 1995) or to confront participants with an uncertain outcome of their service request. In our experiment, we assured immediate handling of their return requests. Another idea would be to vary the outcome of the scenarios with successful and unsuccessful product return scenarios (Mozafari et al. 2021). Future research should explore moderator variables beyond service criticality, such as individual differences, for example, Big Five personality traits or personal innovativeness (Park and Woo 2022; Sindermann et al. 2022) and emotional involvement, which have been shown to significantly influence decision-making processes (Herrero-Fernández et al. 2020). Investigating these factors could provide deeper insights into how personal characteristics and emotional states shape trust in AI-mediated interactions. Additionally, the role of mediator variables should be examined to better understand the relationship between customer trust and AI-MC. Potential mediators include AI trustworthiness (Gillis et al. 2024; Li et al. 2024), AI familiarity (Horowitz et al. 2024), and perceived AI transparency (Hohenstein and Jung 2020), which may help to further clarify the dynamics of trust in AI-mediated interactions.

6 | Conclusion

With the advent of easily accessible generative AI, more and more companies are incorporating its use in their processes to gain efficiency and save costs. Using AI to facilitate CRM processes and to increase efficiency questions how AI-MC affects customer trust in a company. Our research shows that customers perceive an online retailer using AI in CRM as less trustworthy. Interestingly, this effect is particularly pronounced when AI assists a service employee in writing an email to the customer in a product return scenario compared to an email written by AI on behalf of the service employee. This effect is mainly driven by lower perceptions of the online retailer's benevolence and integrity rather than competence. In contrast, we have not found any effect of service criticality on the relationship between customer trust and AI-MC. Our findings shed light on the complex dynamics between transparency in AI-MC implementation in CRM and customer trust, revealing that it is not merely the presence of AI but the way its involvement is framed in customer interactions that significantly influences trust perceptions in an online retailer. Practitioners can thus benefit from our results, especially given the AI EU Act, which proposes that AI-generated content must be made transparent to customers. We hope this research will inspire other researchers to investigate the role of AI-MC further on customer trust and relevant context variables.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** Supporting Information.

Appendix A

Scenario Description and Stimulus Material

Contains the scenario descriptions and stimulus materials used in the study. The scenarios were designed to manipulate the degree of AI agency in CRM communication and the level of service criticality in a product return context. Participants were presented with a screenshot of an email response from an online retailer and asked to imagine themselves as the customer. The email varied in AI agency (complete human agency, shared human/AI agency, or complete AI agency) and service criticality (high vs. low). The following section provides the exact wording of the stimulus materials for two selected scenarios: (a) a high-criticality scenario with complete AI agency (Figure A1) and (b) a low-criticality scenario with complete human agency (Figure A2). The remaining scenarios follow the same structure and can be inferred from the method section in our manuscript.

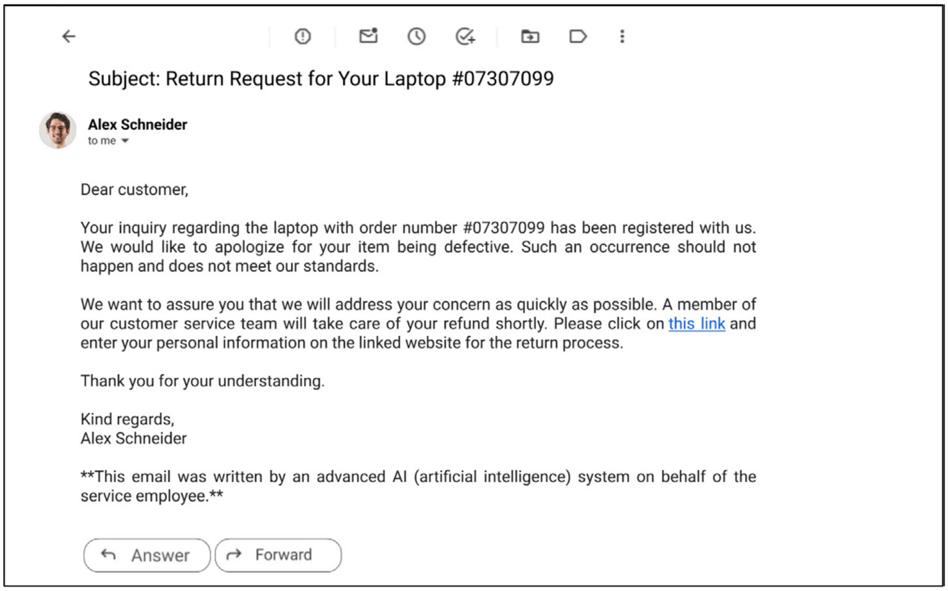
High Criticality Scenario–Complete AI Agency Condition

The following shows you an email communication from an online retailer to a customer. We are interested in how you perceive this email. **Please imagine that you have received this email yourself from an online retailer**.

Background

You recently purchased a **new and very expensive laptop** from an online retailer. Upon first use, you discover that the laptop does not work. However, you urgently need the device to create an important presentation for your job or your studies.

Subsequently, you contacted the online retailer's customer service via email. **This email was written by an advanced AI (Artificial Intelligence) system on behalf of the service employee**. You receive the following reply:



Subject: Return Request for Your Laptop #07307099

Alex Schneider
to me

Dear customer,

Your inquiry regarding the laptop with order number #07307099 has been registered with us. We would like to apologize for your item being defective. Such an occurrence should not happen and does not meet our standards.

We want to assure you that we will address your concern as quickly as possible. A member of our customer service team will take care of your refund shortly. Please click on this link and enter your personal information on the linked website for the return process.

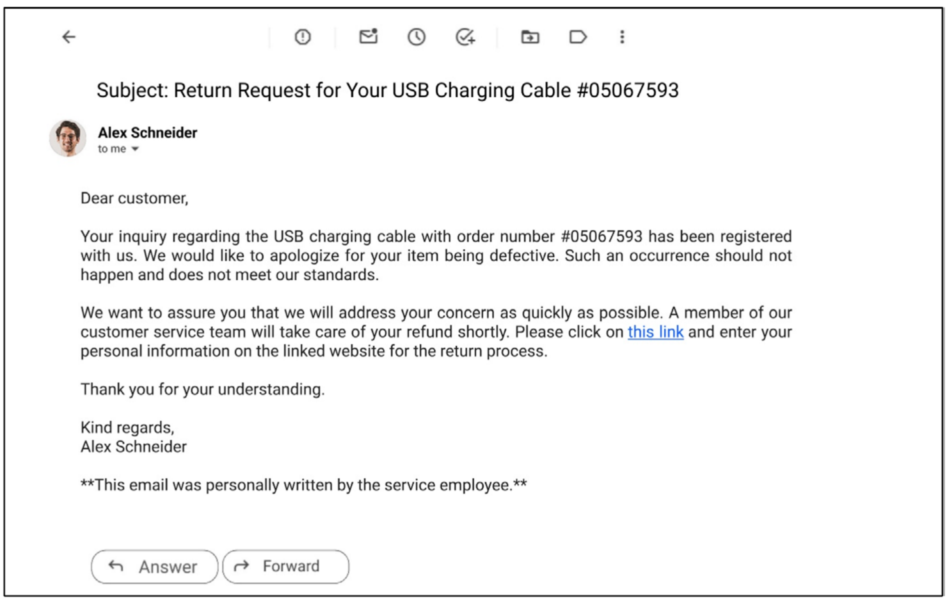
Thank you for your understanding.

Kind regards,
Alex Schneider

This email was written by an advanced AI (artificial intelligence) system on behalf of the service employee.

Answer Forward

FIGURE A1 | Screenshot of the high criticality scenario–complete AI agency condition.



Subject: Return Request for Your USB Charging Cable #05067593

Alex Schneider
to me

Dear customer,

Your inquiry regarding the USB charging cable with order number #05067593 has been registered with us. We would like to apologize for your item being defective. Such an occurrence should not happen and does not meet our standards.

We want to assure you that we will address your concern as quickly as possible. A member of our customer service team will take care of your refund shortly. Please click on this link and enter your personal information on the linked website for the return process.

Thank you for your understanding.

Kind regards,
Alex Schneider

This email was personally written by the service employee.

Answer Forward

FIGURE A2 | Screenshot of the low criticality scenario–complete human agency condition.

Low Criticality Scenario–Complete Human Agency Condition

The following shows you an email communication from an online retailer to a customer. We are interested in how you perceive this email. **Please imagine that you have received this email yourself from an online retailer**.

Background

You recently purchased a **USB charging cable** from an online retailer. **The cable was not expensive, as it was on sale**. Upon first use, you discover that the cable does not work. It is not urgent since you have other charging cables at home, but it is still annoying.

Subsequently, you contacted the online retailer's customer service by email. **This email was personally written by the service employee**. You receive the following reply: